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CONTRIBUTION AND COMBINATION OF DIFFERENT WOOD SECTIONS IN SPECIES RECOGNITION USING IMAGE TEXTURE ANALYSIS METHODS

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Abstract:
The recognition of wood species is a laborious process, which is performed by experts, who attempt to distinguish the different species in different wood sections based on their macroscopic and microscopic characteristics. Most of these characteristics can be observed in the transverse or cross section of woods. According to experts, the next most important surface for wood species recognition is the tangential section while significant information can also be obtained from the radial section of woods. Based on the recent advances in the area of computer vision and pattern recognition, most researchers have proposed image-based approaches attempting to address the problem either in microscopic or macroscopic scale. The main limitation is that in many cases there are some features that are not visible in each wood section. Firstly, we examine the contribution of each section in wood species recognition using two different computer-based texture analysis methods. Furthermore, we compare wood species recognition methods for both grayscale images and colorscale images. Finally, we propose a novel fusion method and we demonstrate that wood species recognition accuracy can be increased by fusing features from different wood sections. For the evaluation of the proposed method, a dataset, namely "WOOD-AUTH", consisting of more than 4272 wood images of twelve common wood species, was used.

Key words: *wood species recognition; wood texture analysis; different wood sections features fusion.*

INTRODUCTION

The recognition of wood species, which is performed by experts, is a laborious procedure because of them having different characteristics, different properties and consequently different money values. In the process of species recognition, the experts classify wood samples by detecting specific characteristics. In any type of operation or activity that uses woods, the species must be carefully considered. In industry, in manufacturing of wood products as well as in construction of residential segments such as roofs, or wood houses the compliance with specific standards is a prerequisite for maintaining security. The correct choice of the desired wood helps a) to ensure the quality of construction and b) to avoid the extra cost of construction.

At each stage of the wooden structures, process recognition is performed by experts and it is primarily based on distinguishing of the macroscopic and microscopic characteristics of woods. First of all, most of these characteristics can be observed in the transverse or cross section of woods. Secondly the tangential section is the next most important surface for wood species recognition and follows the radial section (Bond & Hamner 2002, Jones 2016).

Nowadays, the evolution of imaging technology has positively affected several areas of computer vision. In the case of recognition of species of woods, image techniques based on image processing, texture analysis (Davis et al. 1979) and textural features (Haralick 1979) have significant advantages. Specifically, experts require a long time to train to identify specific wood species while computer based systems training time is short with fast process of recognizing. Furthermore, vision based systems allow simultaneous recognition in different places without extra expenses and with quite good reliability.

Several techniques have been proposed for the recognition of wood species attempting to address the problem either in microscopic or macroscopic scale. In the case of microscopic image analysis researchers aim to identify various microscopic wood features using CCD microscopes and use them as input to the classification system (Cavalin et al. 2013, Yuliastuti et al. 2013). Notable is the method that proposed by Gurau et al. (2013) and based on ImageJ, an image processing program intended for medical microscopy that separate anatomical structures of wood sections and estimate statistical variables. On the other hand, wood recognition approaches based on macroscopic images have recently attracted increased interest, mainly due to their flexibility, simplicity and operability (Hu et al. 2015). Many of wood species recognition use macroscopic grayscale images, co-occurrence matrices (GLCM) and statistical analysis in these images (Tou et al. 2007, Khalid et al. 2008, Wang 2010, Samanta et al. 2015). A similar method for forest species recognition that combines color-based features and GLCM was presented by Filho et al. (2010). Furthermore, two related research works in wood species recognition are presented by Bremanath et al. (2009) that classify ten Indian wood species using the GLCM and Pearson correlation technique. The research approach conducted by Mohan et al. (2014) divides images into blocks using grayscale images.

Then, GLCM features are generated from the above blocks and a correlation formula is used for recognition of wood species.

The main limitation, however, of all above approaches is the fact that they take into account features that are derived from a single section of a wood species. In this paper we examine the contribution of each section in wood species recognition and we propose a novel fusion method that combines features of two different wood sections. To this end, we use two computer-based texture analysis methods: a) using co-occurrence matrices and b) introducing linear dynamical systems.

OBJECTIVE

In this paper we examine the contribution of different wood sections in the procedure of wood species recognition using two different computer-based texture analysis methods. Specifically, we examine the wood sections contribution using co-occurrence matrices (CMs) both for the grayscale images and the colorscale (RGB) images concatenating the extracted features of each channel as described by Barmpoutis and Lefakis (2016). Furthermore, this paper, inspired by literature methodology (Barmpoutis 2017), enables the representation of wood images as histograms of LDS descriptors produced by 2-D patches. Finally, we show that wood species recognition accuracy can be increased by the novel combination of two different wood section features.

MATERIAL, METHOD, EQUIPMENT

The proposed methodology consists of several steps, as is shown in Fig. 1. Capturing wood images, it is important to clarify that sometimes, in small wood specimens it is difficult specifically for non experts to distinguish tangential from radial sections. For this reason, we examine the contribution of sections to wood species recognition using a) cross and b) tangential or radial sections. Subsequently, in this paper we propose wood species recognition rates using the combination of two different sections including one cross section and one of tangential or radial section from the same specimen. Furthermore, we compare wood species recognition methods for both grayscale images and colorscale (RGB) images using two different computer-based texture analysis methods: a) co-occurrence matrices (CMs) and b) linear dynamical systems (LDSs).

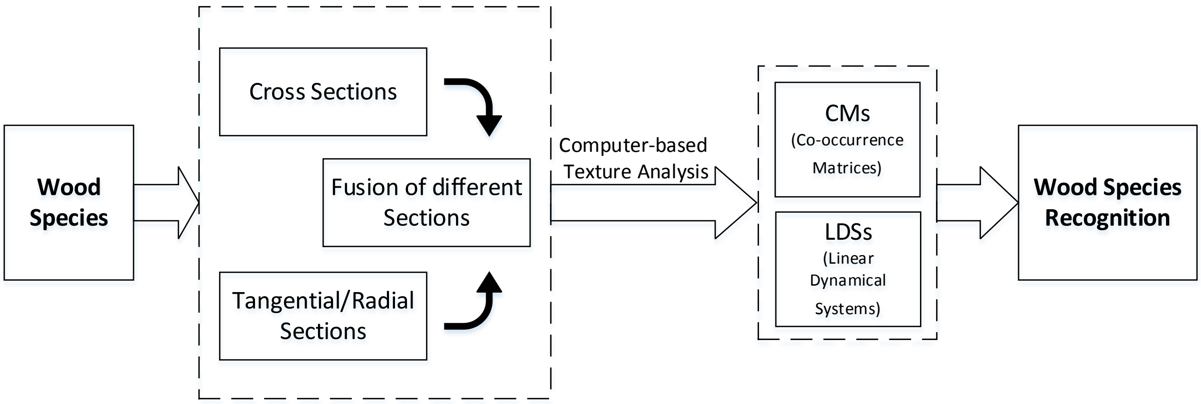

Fig. 1.
Proposed Methodology.

For the purpose of the specific research the database "WOOD-AUTH" was used (Barmpoutis, 2017). This dataset consists of twelve wood species (three softwood species and nine hardwood species) that exist in Greek territory (Tab. 1). The total number of images from cross, radial and tangential wood sections in the dataset is 4272. We have to note that images of this dataset have not been taken by professional photographers and under ideal shooting conditions. Wood images of "WOOD-AUTH" dataset were acquired at the Laboratory of Wood Technology of Forestry and Natural Environment School of Aristotle University of Thessaloniki, Greece and they were taken from distance of 15-20cm using Nikon D3300 digital camera of 24 megapixels. All images size of datset is 400 x 400 pixels.

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Table 1

Wood species of 'WOOD-AUTH' dataset

Botanical Name	Category	**Botanical Name**	Category
Alnus glutinosa	Diffuse-porous hardwood	**Fagus sylvatica**	Diffuse-porous hardwood
Juglans regia	Semi-diffuse-porous hardwood	**Platanus orientalis**	Diffuse-porous hardwood
Ailanthus altissima	Ring-porous hardwood	**Castanea sativa**	Ring-porous hardwood
Fraxinus ornus	Ring-porous hardwood	**Quercus cerris**	Ring-porous hardwood
Robinia pseudoacacia	Ring-porous hardwood	**Cupressus sempervirens**	Softwood
Picea abies	Softwood	**Pinus sylvestris**	Softwood

Texture analysis using co-occurrence matrices and analysis

The use of the co-occurrence matrix is a powerful and widely used texture analysis method. The advantage of the co-occurrence matrix or co-occurrence distribution calculations is that the co-occurring pairs of pixels can be spatially related in various orientations with reference to a) distance and b) angular spatial relationships.

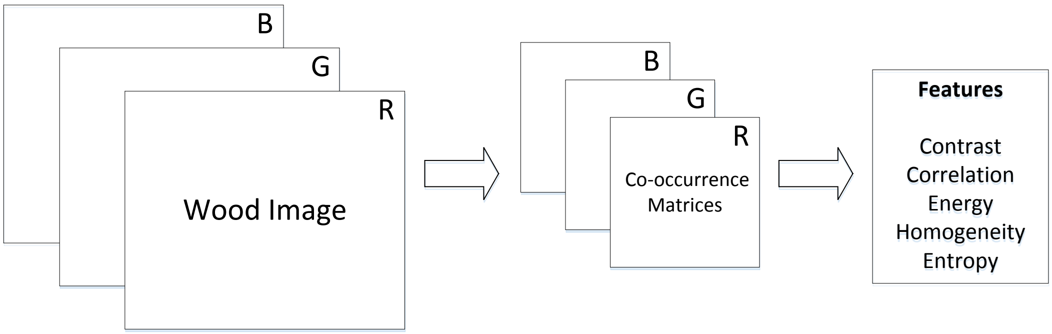

Fig. 2.
Representation of colorscale images (RGB) using co-occurrence matrices and analysis.

In order to use the three channels of RGB images we calculate co-occurrence matrices and features of them for each channel. Co-occurrence matrices are tabulations of how often different combinations of pixel brightness values occur in each channel of an image. To generate co-occurrence matrices we focus on four directions of pixels combinations (0 degrees, 45 degrees, 90 degrees and 135 degrees) and we define the spatial distance of pixels equal to d. For each direction and each channel we extract 5 textural features. The co-occurrence matrices are defined as *G*×*G* matrix for images with *G* values for each channel. Co-occurrence matrices are presented by $C_d(m,n)$ where the first pixel value is m and the second pixel value is *n*. The normalized co-occurrence matrices are represented by:

$$p(m,n) = \frac{1}{\sum pairs \quad of \quad pixels} C_d(m,n) \tag{1}$$

The features that are extracted using each co-occurrence Matrix of colorscale images are the following:

Contrast, for estimation of local variations:

$$Contrast = \frac{1}{(G-1)^2} \sum_{m=0}^{G-1} \sum_{n=0}^{G-1} (m-n)^2 \, p(m,n) \tag{2}$$

Correlation, for estimation of probability of occurrence for a pair of specific pixels:

$$Correlation = \frac{\sum_{m=0}^{G-1} \sum_{n=0}^{G-1} mnp(m,n) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{3}$$

where μ_x, μ_y, σ_x, σ_y are defined by the:

$$\mu_x = \sum_{m=0}^{G-1} m \sum_{n=0}^{G-1} p(m,n) \tag{4}$$

$$\mu_y = \sum_{n=0}^{G-1} n \sum_{m=0}^{G-1} p(m,n) \quad (5)$$

$$\sigma_x = \sum_{m=0}^{G-1} (m-\mu_x)^2 \sum_{n=0}^{G-1} p(m,n) \quad (6)$$

$$\sigma_y = \sum_{n=0}^{G-1} (m-\mu_y)^2 \sum_{m=0}^{G-1} p(m,n) \quad (7)$$

Energy, for estimation of uniformity:

$$Energy = \sum_{m=0}^{G-1} \sum_{n=0}^{G-1} p(m,n)^2 \quad (8)$$

Entropy, for estimation of the statistical randomness:

$$Entropy = \sum_{m=0}^{G-1} \sum_{n=0}^{G-1} p(m,n) \log p(m,n) \quad (9)$$

Homogeneity, for estimation of the distribution of elements:

$$Homogenity = \sum_{m=0}^{G-1} \sum_{n=0}^{G-1} \frac{p(m,n)}{(1+|m-n|)} \quad (10)$$

Texture analysis using LDSs

A dynamic texture can be considered as a multidimensional signal or sequences of images of moving scenes (Doreto et al. 2003). Recently, a method that uses solutions of linear dynamical systems and extracted LDS descriptors was presented and used by Doretto et al. (2003) Ravichandran et al. (2013), Barmpoutis et al. (2014) and Dimitropoulos et al. (2015). This method has been used in literature for categorizing dynamic textures in video sequences and for fire detection in videos.

By the assumption that a wood image consists of successive, interrelated and repetitive pixels that are particular for each species of wood we take the advantage of the dynamic texture theory and we introduce the descriptor for wood species recognition in static images. In this way the calculated descriptors (LDSs) solving dynamical linear systems contain both appearance and dynamics information. In both cases of grayscale and colorscale wood images, the dynamic texture can be represented with a 2-D matrix. In colorscale images the matrix is implemented if we concatenate the three channels of RGB images as is shown in Fig. 3.

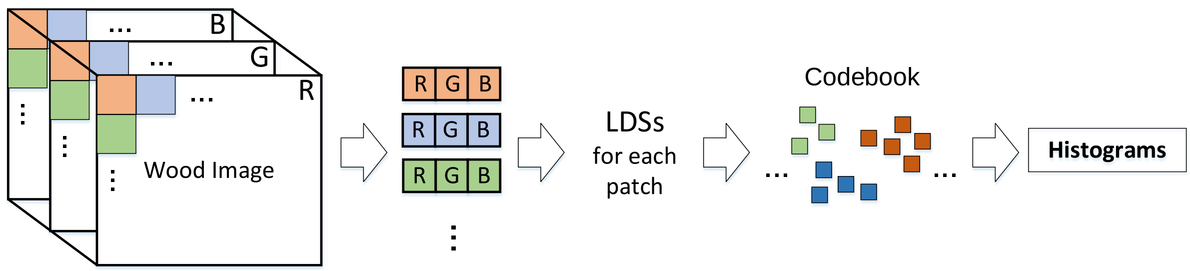

Fig. 3.
Representation of colorscale images using linear dynamical systems.

According to Doretto et al. (2003) the stochastic modeling of both signal's dynamics and appearance is encoded by two stochastic processes, in which dynamics are represented as a time-evolving hidden state process $z(t) \in \Re^N$ and the observed data $y(t) \in \Re^s$, (e.g., *s* indicates the number of pixels in a pacth), as the output of the system:

$$z(t+1) = Az(t) + Bv(t) \quad (11)$$

$$y(t) = C^0 + Cz(t) + w(t) \quad (12)$$

Where $A \in \Re^{N \times N}$ is the transition matrix of the hidden state, $C \in \Re^{s \times N}$ maps the hidden state to the output of the system, $C^0 \in \Re^s$ is the mean value of pixels intensities, and $w(t) \sim N(0,R)$ and $Bv(t) \sim N(0,Q)$ are the measurement and process noise, respectively (Doretto et al. 2003, Ravichandran et al. 2013).

Given a wood image *W*, we consider that it consists of non-overlapping patches that contain periodic spatially-evolving (instead of time-evolving data) characteristics whose size is *p×(p×m)*, where *p* indicates the size of patch (in our experiments *p=3*) and *m* is the number of image channels and each patch consists of *s* pixels. If the image is grayscale then *m* is equal 1. To this end, on the assumption that a wood image is considered as a sequence of successive, interrelated and repetitive pixels, it is divided into non-overlapping patches *y*:

$$Y = [y(1) - C^0, ..., y(p) - C^0] = USV^{\mathrm{T}} \tag{13}$$

$$C = U \text{ and } Z = \Sigma V^T \tag{14}$$

The estimated states $Z = [z(1), z(2), ..., z(p)]$ of the system and the matrix A can be computed using least-squares as $A = [z(2), z(3), ..., z(p)][z(1), z(2), ..., z(p-1)]^{pseudoinverse}$, where $Z^{pseudoinverse}$ represents the pseudoinverse of *Z*. Then, each LDS descriptor *M* is defined by *A* and *C.* To solve the problem of wood species recognition there is the need to define the similarity between two LDS descriptors. In the proposed method we adopted the non-Euclidean distance that is based on the subspace angles (Doretto 2003). The calculation of the subspace angles between the two LDSs is performed by first solving for *P* from the Lyapunov equation $A^T PA - P = -C^T C$, where:

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix}, A = \begin{bmatrix} A_1 & 0 \\ 0 & A_2 \end{bmatrix}, C = \begin{bmatrix} C_1 & C_2 \end{bmatrix} \tag{15}$$

The cosine of the subspace angles is calculated by the following formula:

$$\cos^2 \theta_i = i_{th} eigenvalue(P_{11}^{-1} P_{12} P_{22}^{-1} P_{21}) \tag{16}$$

Using the subspace angles, the Martin distance between M_1 and M_2 is defined as:

$$Martin_{distance}(M_1, M_2) = -\ln \prod_i \cos^2 \theta_i \tag{17}$$

The main advantage of LDS descriptors is that they contain both appearance and dynamics information that is represented by *C* and *A* respectively. In the next step we use clustering which is a useful grouping method of data. The LDS descriptors are feeding into K-medoids and using Martin distance we are estimating cluster centers that represent codewords in the codebook. Each wood image in the training set is represented by the distribution of codewords (histograms). Histograms are the features that will be used for classification of each wood specimen.

Concatenation of different section features

Introducing a fusion method that uses both cross and tangential or radial sections we concatanate features that are derived from each of above sections as shown in the following equation:

$$f = [f_T, f_{TR}] = [f_{T1}, f_{T2}, ..., f_{TS}, f_{TR1}, f_{TR2}, ..., f_{TRS}] \tag{18}$$

Because the new feature vector has the double size on comparison to the previous methods, we apply a dimensionality reduction keeping the half components of the feature. The advantages of the above reduction are related to retain to the important components of wood sections features and to hold the computational cost of the proposed method at low levels. The main linear technique for this is the principal component analysis (PCA) that performs a linear mapping of the data to a lower-dimensional space in such a way that the variance of the data in the low-dimensional representation is maximized (Jolliffe 2002). PCA linearly transform features in order to remove redundant dimensions, and generates a new set of variables called principal components. Using PCA we set the same size to all feature vectors for each method and then they are feed to an SVM classifier.

RESULTS AND DISCUSSION

In this section we present a detailed experimental evaluation of wood species recognition using different wood sections in the “WOOD-AUTH” database (Tab. 2). The goal of the experimental evaluation is three-fold. Firstly, we compare wood species recognition rates using cross sections and tangential or radial sections. Secondly, we aim to show that the use of two wood sections (cross and tangential or radial) improves wood species recognition. Furthermore, we compare the above implementations using grayscale and colorscale images and two different texture analysis methods. In our experiments we follow the k-fold cross-validation scheme using SVM classifier. The wood species dataset is randomly split into k (in our experiments, k=5) mutually exclusive subsets of approximately equal size. In the k-fold cross-validation, k-1 subsets are used as training data and the remaining single subset is used for testing the model. We repeat the above procedure 5 times.

Table 2

Wood images of 'WOOD-AUTH' dataset

Contribution and combination of different wood sections using Co-occurrence Matrices

In Fig. 4, we present experimental results using different wood sections and co-occurrence matrices for wood species recognition. As we can notice easily the proposed method using two different wood sections, including one cross section image and one tangential or radial section image, produces the best results. Recognition rates using grayscale images can reach to 74,5% and 83,7% using colorscale images. Experimental results show that there is significant improvement using the original color wood images instead of the grayscale images. This fact really indicates the significance of information that are exist in three channels of colorscale images. It is obvious that when we use tangential or radial sections for wood species classification the recognition rates between the grayscale wood images and colorscale (RGB) wood images are similar, due to the lower importance and quality of characteristics in these sections.

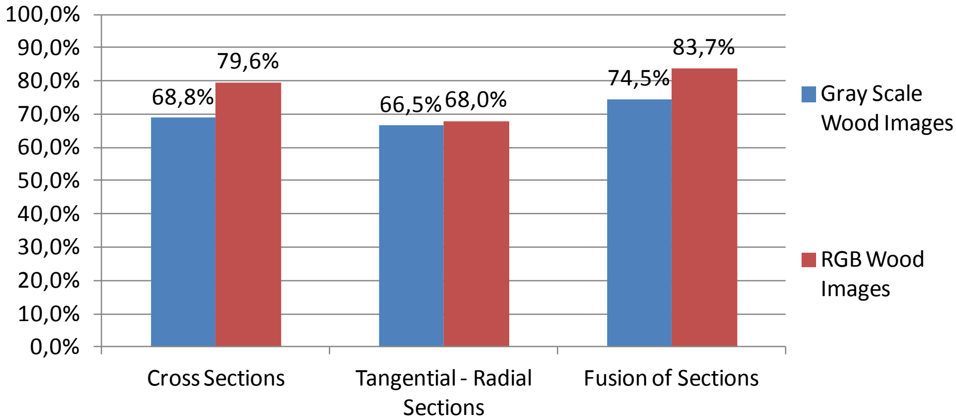

Fig. 4.
Contribution and combination of different wood sections using co-occurrence matrices in grayscale and colorscale wood images.

Contribution and combination of different wood sections using LDSs

By taking advantage of the fact that static wood images contain periodic spatially-evolving characteristics, in Fig. 5 we present wood species recognition results using LDS descriptors, in grayscale or colorscale wood images and in different wood sections. As is it clearly shown, the use of grayscale images of tangential or radial sections produces the lowest recognition rates for both techniques. The classification rate using cross sections and grayscale images is 76,8%, while the recognition rate is lower, 70,6%, using tangential or radial sections. It is worth mentioning that when we use colorscale images and LDS descriptors the recognition rates are slighty increased. They reach to 79% and 72,2% for cross sections and tangential or radial sections, respectively.

It is obvious that the use of LDSs produces in the most cases better results than using co-occurence matrices. The experimental results obtained in this study show the great potential of the proposed method using two different wood sections. Specifically, wood species recognition outperforms with an average true positive rate of 86,1% when we fuse LDS descriptors that are derived both from cross sections and tangential or radial sections. The above fusion using LDS descriptors shows that it improves significantly the robustness of the algorithm, increasing, however, its recognition ability.

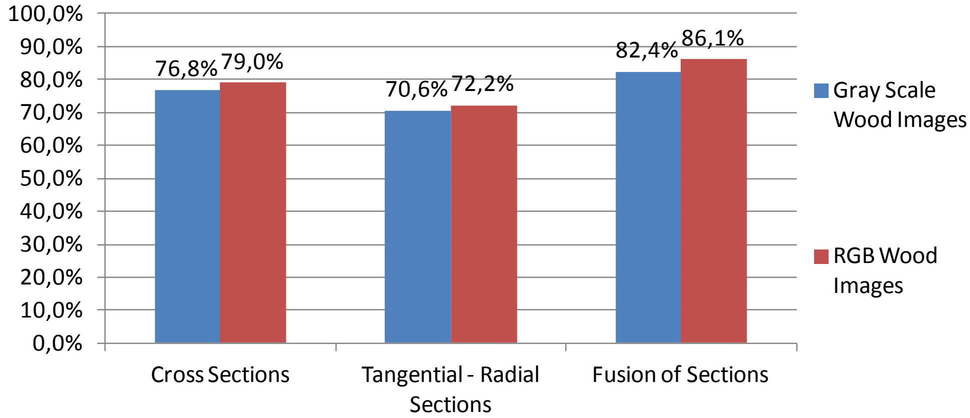

Fig. 5.
Contribution and combination of different wood sections using LDSs in grayscale and colorscale wood images.

CONCLUSIONS

In this paper we presented a detailed comparison and a fusion method for wood species recognition using different wood sections. We used grayscale and colorscale wood images and we compared two different texture analysis methods. In our study we showed that images containing wood cross sections provide higher classification rates than radial and tangential sections. Additionally, the experimental results obtained in this study using the combination of features that are retrieved from two different sections including a cross section and a tangential or a radial section show the great potential of the proposed method. Moreover, in the future we aim to apply the proposed methodology using multidimensional image analysis and higher order systems for texture analysis. Finally, a new challenge for the proposed method would be its application to different wood species.

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